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ARTIFICIAL INTELLIGENCE IN ORAL MEDICAL RADIOLOGY & CLINICAL DECISION SUPPORT SYSTEMS (CDSS)

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ABSTRACT - Artificial Intelligence (AI) is an emerging technology in dentistry that has the potential to transform the field. By analyzing dental radiology images, AI algorithms can help detect early-stage oral cancer, predict implant failure, and identify anatomical structures accurately. Furthermore, AI integration in Clinical Decision Support Systems (CDSS) can assist dentists in making more informed decisions by analyzing patient data and medical records to suggest the most effective treatment options. AI-powered chatbots and virtual assistants can provide patients with real-time assistance and support, improving access to care and enhancing patient satisfaction. With these capabilities, AI has the potential to revolutionize dentistry by reducing the need for invasive procedures, improving efficiency, and providing personalized care. It is exciting to think about the many possibilities that AI can bring to the dental practice, and how it can shape the future of the industry.

Keywords *– AI, Machine Learning, Dentistry, Imaging, Diagnosis*

I. INTRODUCTION

In a wide number of businesses, including the dental and medical fields, artificial intelligence has transformed from being viewed as a faraway and fantastical fantasy to a realistic reality. Particularly in oral and maxillofacial radiology, artificial intelligence has been used to process radiographic images in dentistry. At a summer workshop held at Dartmouth in 1956, the idea of artificial intelligence was first presented [1]. This paved the way for further investigation into areas like neural networks, natural language processing, and computation theory. The field faced substantial obstacles despite early optimism. Between 1974 and 1980 and between 1987 and 1993, there were two instances of the so-called "artificial intelligence winter," which was marked by decreased funding and interest. Unrealistic expectations and technological barriers to data accessibility contributed to this downturn [2] .

Through numerous conveniences like AI-based speakers and content recommendation systems, artificial intelligence is subtly influencing every part of our life. Deep learning's development presents fascinating possibilities for automating image processing in the dental and medical fields. In a variety of AI fields, including data mining, robotics, natural language processing, and medical image analysis, significant advancements have been made. Yet, questions have been raised about the legitimacy of AI diagnosis and the basis for AI judgements. Consequently, it is crucial to take into account the idea of explainable artificial intelligence and the requirement for human intervention in the development of artificial intelligence. Also, it is critical to address harmful applications of AI in the diagnosis field.

II. MACHINE LEARNING & DEEP LEARNING

A branch of artificial intelligence known as "machine learning" studies how computer models can be improved via experience alone, rather than through explicit instructions. To create models that are capable of making predictions or choices, this process demands the usage of sample data. Supervised, unsupervised, and reinforcement learning are the three main divisions of machine learning. In supervised learning, labels are learned for each input, and classification and regression issues are the key topics. Expert radiologists must perform the labelling or annotation in order to facilitate supervised learning of diagnostic pictures. Unsupervised learning, on the other hand, uses algorithms that discover patterns from unlabeled data to answer issues like clustering and distribution estimates. Reinforcement learning algorithms learn through positive or negative feedback in dynamic situations and are utilized in a variety of industries such as robotics, video games, and computer vision [3] .

Deep learning is a subset of machine learning that was developed in the 1980s as a result of neural network research. Deep learning systems are unique in their capacity to derive high-level abstractions and complex features from big data through a combination of several nonlinear transformations using artificial neural networks, though they share a common strategy with conventional machine learning in using data to learn models [4]. A brand-new technology that used a backpropagation algorithm to self-learn the data was introduced in 1989. Since then, the utilization of high-performance graphics processing units, the growing accessibility of huge data, and deep learning's capacity to address the overfitting issue—where predictions match the training set too closely—have all contributed to the technology's fast expansion.

Recent developments in artificial intelligence have been facilitated by deep learning architectures like convolutional neural networks (CNNs). They are most frequently used to analyse huge, complicated images like those used in medical imaging. A schematic representation of deep learning training for caries segmentation in periapical radiographs is shown in Figure 1. By repeated steps, the deep neural network continuously reduces the error between prediction and ground truth labels in order to learn from the data. Error minimization occurs gradually through the use of minibatch error differentiation (partitioned data set). CNNs have been employed as a key element of networks in the field of oral and maxillofacial radiology.[5]

Generative adversarial networks (GANs) have been introduced. These models are made up of two networks that are trained by competing against one another in a game, and they produce new data that mimics the original data. The radiographic pictures have been subjected to enhanced GAN models utilizing CNNs [6]. CNNs can be utilized for segmentation, detection, and classification in the field of radiology (Figure 2). In order to classify something, you must first determine whether a sickness is there or not, as well as what kind of malignancy it is. Deeper and more complicated CNN models have been developed as a result of improvements in computing power to address classification issues in radiographic image processing [7]. In radiographic image analysis, detection is done to locate areas with lesions or specific anatomical structures. The CNNs used for classification tasks and those used for detection tasks are fundamentally identical [8]. However, other layers with extra features have been added to CNNs for disease identification, such as a region proposal or regression. Many anatomical features or lesions in pictures recorded using a variety of modalities, including plain radiography, CT, MR, and ultrasound imaging, have been segmented using a technique called segmentation. [9]

Figure 1*: Schematic view of deep learning with caries segmentation in periapical X-Ray*

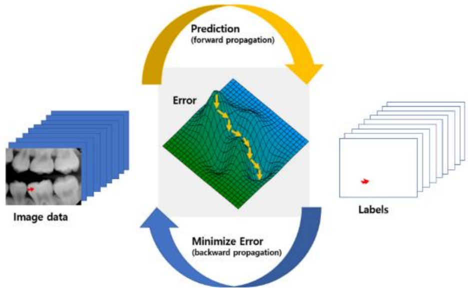
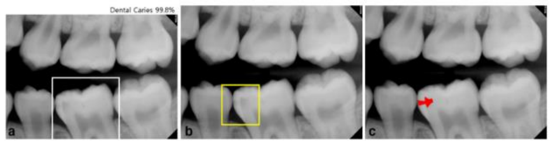


Figure 2*: a. Dental Caries is present in the rectangular box on the image (classification). b. Dental Caries is detected in the square box (detection) c. A Dental Caries is segmented on the image (Segmentation)*



III. PREPARATION OF DATASETS FOR ARTIFICIAL INTELLIGENCE

Collecting & Labelling Data - In practice, the implementation of artificial intelligence for automated interpretation can be very expensive. To achieve high accuracy, a large amount of data is required for massive-scale learning. This data must be processed and organized through a process known as data curation, which involves the integration and standardization of data from various sources. For radiographic images, this process includes data anonymization, representative data checking, format standardization, noise reduction, segmentation of the region of interest, and annotation. Accuracy is essential in artificial intelligence studies that use deep learning, and to achieve this, it is necessary to have a high-quality data set with accurate labels. Ground truth values, also known as reliable references, are critical in deep learning, and correct labels generated by experts serve as a form of ground truth. [10]

Two methods can be used to generate labels. One way is for a radiologist to make annotations through image review, while the other is to use information from radiology reports. However, the former method can be time-consuming and labor-intensive, and there may be differences in the annotations made by different readers, particularly in two-dimensional radiographic images where structures overlap. In 2D radiographic images such as periapical and panoramic photographs, it is often challenging to clearly distinguish and outline three-dimensional anatomical structures (as seen in Figure 3). The latter method may require re-testing the correctness of the labels. The choice of labeling method depends on the task at hand.

When radiologists create labels, several points should be considered. First, to generate massive quantities of data, it is usually necessary for a team consisting of several radiologists to label the images, and the standards between radiologists may differ during this process. Therefore, establishing a consensus for labeling is important for ensuring an adequate ground truth. Second, the format of the labels and the labeling tool should reflect the task content and the deep learning model being used. Radiologists should communicate with the engineers who develop the code for deep learning applications to establish the type of label required.

Acquiring an extensive dataset of high-quality data is ideal for optimizing the performance of a deep learning application. However, obtaining high-quality labeled data can be costly and time-consuming, and it may not be possible to obtain a sufficient number of case samples for some studies. To address this issue, data augmentation can be used, which involves altering the data set in a way that changes the data representation while keeping the label the same. Possible transformations include cropping, flipping, rotation, translation, zooming, skewing, elastic deformation, and modifying the contrast or resolution (as seen in Figure 4) [11]. Care should be taken to avoid removing the region of interest through the augmentation process, which can degrade the performance of the deep learning model. Recently, studies have been launched to solve the issue of data scarcity in various classification, detection, and segmentation problems by using synthetic data augmentation through GANs.

***Figure 3**: Example of complex labelling of dental panoramic radiography. In two-dimensional radiographs where structures overlap, it is often difficult to clearly distinguish and outline three-dimensional anatomical structures. Green: Teeth, Pink-Implants, Sky – Prosthodontics, Brown – Endodontic Filling, Red – Dental Caries.*

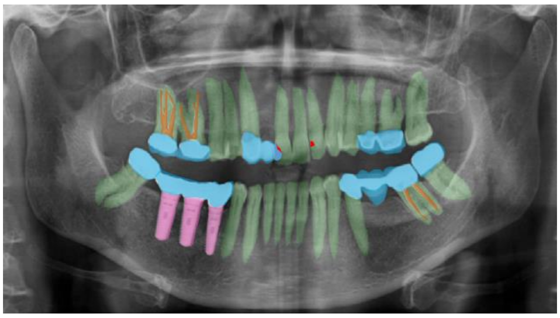
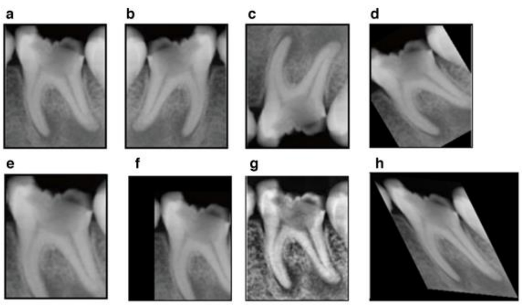


***Figure 4**: Data augmentation example of periapical X-Ray a. Original Image b, c. Flip d. Rotation, e. Zoom, f. Translation, g. Contrast adjustment, h. Elastic deformation. Note that apical lesion is removed in d, e, and f, which can degrade performance of periapical lesion detection model.*

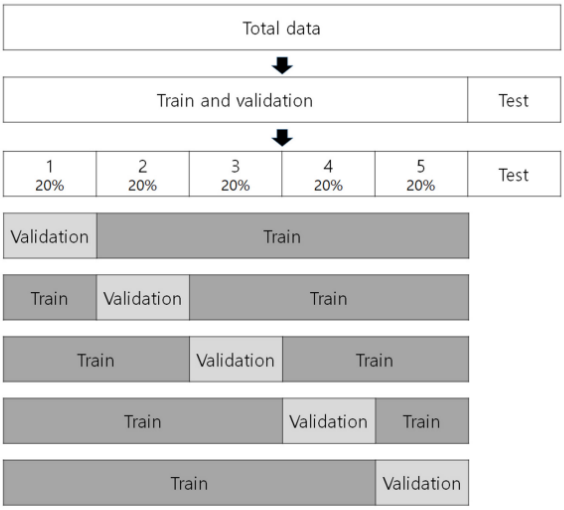


Diving Data for Learning Process - The process of utilizing labeled data for machine learning typically involves dividing the data into three distinct sets: training, validation, and test sets. The training set is employed to train and adjust the parameters of the learning model, while the validation set is used to monitor the model's performance during training and to search for the best possible model. Finally, the test set is used to evaluate the ultimate performance of the model. It is of utmost importance to ensure that there is no overlap between the training/validation and test sets, and the size of the data set required for each step depends on the nature and complexity of the task at hand.[12]

In cases where the available data set is small, cross-validation can be conducted to estimate and generalize the performance of the training model in the training phase. In k-fold cross-validation, the training data set is divided into k equal subsets (as shown in Figure 5). One data subset is kept aside as the validation set, while the others (k-1) are utilized as a cross-validation training set. The model is then trained using the training set, and its performance is measured with the validation set [13]. This process is repeated k times, with the validation set being changed each time. The final performance is the average of the k measured performances.

In some studies, the validation set is omitted, and the data are separated into training and test data sets. However, caution must be exercised in selecting the appropriate size of the training and test sets to ensure that the model's performance is reliable and generalizable.

***Figure 5**: An example of fivefold cross-validation. Total data separate into trains, validation, and test data sets for a study on artificial intelligence*



IV. ARTIFICIAL INTELLIGENCE IN OMF RADIOLOGY

A scientist has conducted a review of English language studies related to Artificial Intelligence in the field of OMF radiology using various relevant databases. Among the 25 articles found, 12 were focused on teeth, 2 on dental tissues, and 2 on osteoporosis. The results indicated that Convolutional Neural Networks (CNN) were the primary network component used. Over time, the number of published papers and training datasets has increased in various dentistry fields.

The study conducted from 2015-2019 encompassed various fields in dentistry such as general dentistry, cariology, endodontics, periodontology, orthodontics, dental radiology, forensic dentistry, and general medicine. The most commonly analyzed image types were panoramic radiographs, periapical radiographs, and cone-beam CT or conventional CT, with dataset sizes ranging from 10 to 5166 images. [14,15,16]

The review analyzed 50 studies to investigate the current clinical applications and diagnostic performance of Artificial Intelligence in dental and maxillofacial radiology. The studies used various image types, including periapical radiographs, panoramic radiographs, cephalometric radiographs, cone-beam CT (CBCT) images, intraoral photographs, and 3D images (CR/MRI). Most studies focused on applications for automated localization of cephalometric landmarks, diagnosis of osteoporosis, classification/segmentation of maxillofacial cysts and/or tumors, and identification of periodontitis/periapical disease. The performance of Artificial Intelligence models varied across different algorithms.

The review also covered the basic concepts of Artificial Intelligence, machine learning, deep learning, training of neural networks, learning program and algorithms, and fuzzy logic. The authors suggested future prospects of Artificial Intelligence in radiomics, imaging biobanks, and hybrid intelligence in dental and maxillofacial radiology.

Radiographic Diagnosis - In the realm of OMF radiology, there have been various studies conducted on the use of artificial intelligence (AI) for diagnosing a wide range of conditions, including dental caries, periodontal disease, osteosclerosis, odontogenic cysts and tumors, and diseases of the maxillary sinus or temporomandibular joints.

In the 1990s, an early form of AI was developed by White at UCLA, who created a system called "ORAD" in 1995. This system has since been updated to ORAD II (*http://www.orad.org/cgi-bin/orad/index.pl*), which provides a list of differential diagnoses for OMF diseases based on a patient's clinical and radiographic features (see Figure 6) [17]. While ORAD represents an early step in the application of AI for diagnostic purposes, recent studies have focused on the use of deep learning for diagnosing various dental conditions (see Figure 7).

Chang et al.[18] developed an automatic method for staging periodontitis using a deep learning hybrid approach on dental panoramic radiographs, which combined a deep learning architecture with conventional computer-assisted diagnosis (CAD). Their AI system demonstrated high accuracy and reliability in diagnosing periodontal bone loss and staging periodontitis according to the amount of alveolar bone loss. However, an important consideration for AI studies is the quality of data used for training the system. Accurate readings from OMF radiologists are crucial for refining the data used for training AI systems, since diagnostic accuracy can vary depending on the observer's level of experience and skill.

To obtain reasonable results, researchers studying automatic readings using AI must use refined data, such as readings from experienced OMF radiologists. Looking forward, the use of AI in OMF radiology holds great promise for improving the accuracy and speed of diagnoses, and may eventually lead to the development of entirely new diagnostic tools and techniques.

Figure 6*: ORAD II web interface*

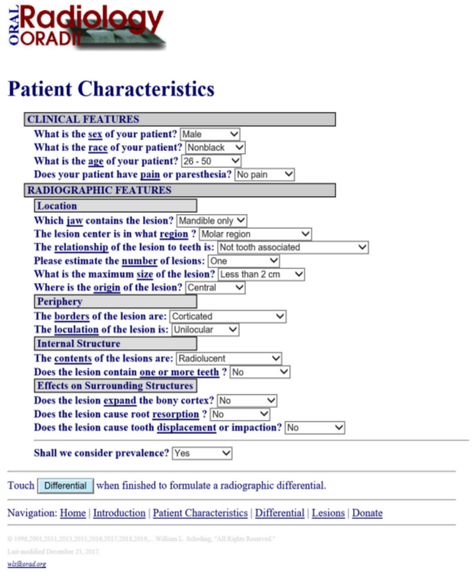
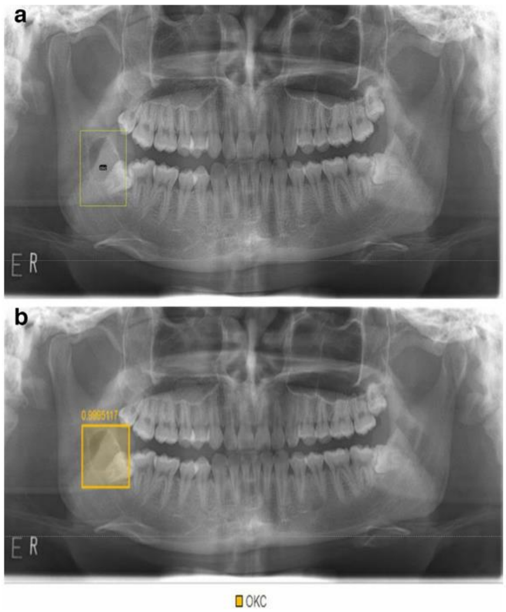


Figure 7*: (a) Odontogenic keratocyst (OCK) is labelled at the tight posterior mandible on a panoramic radiograph. (b) The lesion is automatically detected using deep learning*

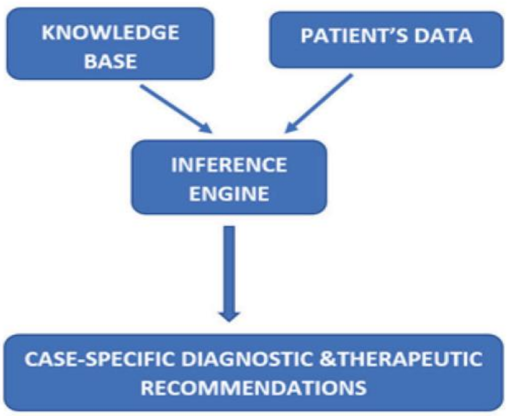


V. CLINICAL DECISION SUPPORT SYSTEMS (CDSS)

CDSS, or Clinical Decision Support Systems, are interactive computer programs powered by AI that aim to aid health professionals in making decisions (Figure 8). The fundamental components of a CDSS consist of a dynamic knowledge base and an inferencing mechanism, which employ medical logic modules based on a language such as Arden Syntax. These systems use clinical knowledge to evaluate patient data and make decisions regarding the diagnosis, prevention, and treatment of orofacial disorders. CDSS applications can be independent or can operate alongside other tools like electronic dental records, order entry systems, or radiology systems.

Moreover, CDSS can inform dentists about potentially dangerous conditions for a patient, such as drug allergies, or remind them of routine tasks, like screening for oral cancer in smokers or periodontal disease in patients with diabetes. Additionally, CDSS can execute tasks, such as the administration of prophylactic antibiotics when appropriate. These varied applications encompass radiology systems and patient education tools, which provide dentists with additional support. By ranking and weighing the related parameters, this intelligent system has the potential to assist experts in making the final decision in differential diagnosis when presented with several possible alternatives, as well as in multi-diagnosis cases where patients have multiple illnesses concurrently. This system intelligently provides specialists with necessary prognoses, including the prediction of lesion susceptibility to malignancy and proposes appropriate measures. Consequently, a clinical decision support system can be employed for the detection and diagnosis of oral cancer.

Figure 8*: Components of CDSS*



Determination of Clinical Parameters - The determination of tooth prognosis involves a review of various factors, including medical history, dental history, family history, social history, extraoral examination findings, intraoral examination findings, radiographic findings, occlusal examination findings, and diagnosis by clinical faculty from different fields in dentistry. Following extensive discussions among the faculty members, 17 critical parameters, including medical and dental conditions, hard tissue, and periodontal, endodontic, prosthodontic, and orthodontic conditions, were identified for the training dataset for machine learning. An example of these parameters can be seen in Figure 9. These parameters were selected based on their weight on tooth prognosis, essential for considering an ideal treatment plan. The data on each parameter were then entered into an Excel sheet using electronic records available in a purchasable software called axiUm, along with case presentation documents.

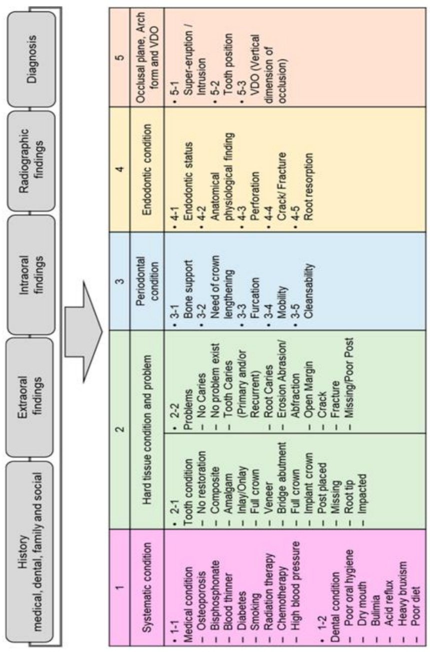


Figure 9*: 17 Key parameters used for determination of tooth prognosis*

Analysis of AI Machine Learning Models - The data obtained from the Excel sheet was preprocessed using a pipeline in this study to convert the data into vectors that could be used for training and testing the AI models. Three AI machine-learning methods were trained using this preprocessing pipeline, namely, (1) a gradient boosting classifier, (2) a decision tree classifier, and (3) a random forest classifier. The performance of these methods was evaluated in terms of accuracy against the gold standard data.

(1) The gradient boosting classifier is a boosting procedure that can be applied to arbitrary differentiable loss functions. A gradient boosting decision tree is an effective and accurate technique used for regression and classification problems in various domains. This method helps in reducing errors by decreasing bias.

(2) The decision tree classifier is a non-parametric supervised learning method employed for classification and regression. This method aids in creating a model that predicts the target variable's value by learning simple decision rules inferred from the data features. A tree can be considered as a piecewise constant approximation.

(3) The random forest classifier is a non-parametric supervised learning method used for classification and regression. This method is designed to create a model that predicts the target variable's value by learning simple decision rules inferred from the data features. A tree represents a piecewise constant approximation, and it is a commonly used algorithm for predicting factors through simple measurement. The objective was to create a model that accurately predicts the target variable's value by employing a piecewise constant approximation

VI. CONCLUSION

To summarize, the application of Artificial Intelligence (AI) in dentistry has immense potential to improve the accuracy, efficiency, and quality of dental treatment. By leveraging cutting-edge technologies like machine learning algorithms, computer vision, and predictive analytics, dental professionals can diagnose and treat a range of dental conditions with greater precision and speed. This can lead to reduced human errors and increased productivity and profitability of dental practices, ultimately benefiting both patients and practitioners. However, it is important to note that AI should not replace human expertise but should be used as a complementary tool to enhance the skills and knowledge of dental professionals. As the field of AI continues to evolve, it is exciting to see how it will revolutionize dentistry and bring about positive changes in patient care.

However, the integration of AI in dentistry also brings up ethical and privacy concerns, which must be addressed. The risk of data breaches, loss of privacy, and discrimination always exists with any technology. Hence, it is crucial to establish strict security protocols and regulations to ensure the safe and responsible use of AI in dentistry.

In conclusion, the use of AI in dentistry has significant potential to enhance patient care. However, it is imperative to implement AI technology with caution and respect for patient privacy and rights. By doing so, we can leverage the full potential of AI in dentistry and create a positive impact on patient outcomes.

VII. CONCLUSION

In conclusion, the journal underscores the importance of incorporating artificial intelligence (AI) and computerized decision support systems (CDSS) into dental radiology to improve the precision and effectiveness of diagnostic and treatment planning. According to the study, these technologies can greatly enhance patient outcomes by automating procedures such as image processing and providing real-time decision support. It's crucial to remember that these technologies should be used in addition to human skill rather than as a replacement. To ensure their ethical and safe usage, it is necessary to carefully prepare and implement these technologies. Therefore, the journal emphasizes the need for additional study and development to maximize the use of AI and CDSS in dental radiology and enhance patient care

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